Pattern Matching based Vehicle Density Estimation Technique for Traffic Monitoring Systems

Sakthidasan Sankaran
Department of Electronics and Communication Engineering,
Hindustan Institute of Technology and Science, India
k.sakthidasan.1983@ieee.org

Abstract: *Due to increase in vehicle density, the road traffic estimation aids in enhancing the traffic management centre's performance and their applications. The analysis of traffic surveillance based on video is an active research area that has varied range of applications in Intelligent Transport System (ITS). In specific, urban environments are much more challenging on comparing highways due to the placement of cameras, vehicle pose, background clutter, or variation orientations. There were several techniques employed so far for the process of traffic monitoring using pattern matching, however there were some limitations like reduced rate of accuracy and increased error rate. So as to overcome this, an efficient method is proposed. The main intention of this proposed approach is to monitor the density of traffic and to estimate the vehicle density using Pattern Matching for Vehicle Density Estimation (PMVDE) scheme. In this paper, the pattern matching based vehicle density estimation is employed for enhancing the detection of accuracy thereby reducing the rate of error. The region of interest of an image that is extracted from the video input is being analysed by this process. These two processes are employed in region of interest extracted image for decreasing the density detection errors. This approach attains less false positive rates and error rate, however this in turn influences the accuracy, precision, recall, F-score, and true positive rates and offers enhanced outcome on comparing other techniques.*

Keywords: *Pattern matching, traffic estimation, vehicle density, region of interest, feature extraction.*

Received August 25, 2020; accepted June 16, 2021
https://doi.org/10.34028/iajit/19/4/1

1. Introduction

The estimation of road traffic density specifies the concentration of vehicles in the road and in turn estimate the traffic free flow. This is employed for attaining necessary data from Intelligent Transportation System (ITS) for routing the vehicle, planning the traffic, traffic regulation, network traffic arrangement, perusing vehicle broadcasting [7, 11]. The traffic density is employed for computing the initial stage of notice, secure application scheduling, and system signaling. On using this methods of density estimation, the driver in turn chooses the route that are appropriate for avoiding the traffic, the traffic is then analyzed by means of camera in several cases because of weather conditions the vehicle is not correctly recognized [15].

The road density accompanied by the vehicles are achieved from the video. The flow of traffic detection is much more significant approach for evading the delays and accidents [5]. Digital image processing is employed for acquiring the video and the videos are divided into frames. The image of road is being captured and in turn detects the speed of vehicles [14]. The vehicle is then counted as an occlusion of multiple vehicles from the traffic image and a methodology is introduced for detecting the shadowed vehicles [19]. The vehicle is then identified by means of lighting the headlights, which is distracted for further processing of an image. The pattern matching is employed for recognizing the history of data vehicle. The pattern present is associated with older patterns for identifying the estimation of density in the road. The digital image processing is employed for the extraction of Region of Interest (ROI) of vehicle. The ROI is extracted and in-turn the feature matching is carried out for the identification of vehicle [12]. The analysis of traffic surveillance based on video is an active research area that has varied range of applications ITS. Typically, urban environments are much more challenging on comparing highways due to the placement of cameras, vehicle pose, background clutter, or variation orientations. There were several techniques employed so far for the process of traffic monitoring using pattern matching, however there were some limitations like reduced rate of accuracy and increased error rate. In order to overcome this, an efficient pattern matching method is proposed.

1.1. Problem Statement

Typically, urban environments are much more challenging on comparing highways due to the placement of cameras, vehicle pose, background clutter, or the variation orientation. There were several techniques employed so far for the process of traffic monitoring using pattern matching, however there were some limitations like reduced rate of accuracy and increased error rate. So as to overcome this, an efficient method is proposed.

1.2. Objective

The main intention of this proposed approach is to monitor the density of traffic and to estimate the vehicle density using Pattern Matching for Vehicle Density Estimation (PMVDE) scheme. This in turn addresses the error rate.

1.3. Organization

The remaining portion of the manuscript is systematized as follows: Section 1 is the detailed narration of various existing techniques employed so far. Section 3 illustrates the proposed methodology description. Section 4 is the detailed depiction of performance analysis for proposed system. At last, the overall conclusion is summarized in section 5.

2. Related Works

Chung and Sohn [6], suggested for traffic density estimation depending on the image analyzed over the deep Convolutional Neural Network (CNN). The supervised learning was employed for the extraction of features and in turn process it by means of CNN.

Tayara *et al*. [16], proposed an approach of Automated Vehicle Detection and Counting System (AVDCS) focusing mainly on the computation of high-pixelated images with the utilization of regression neural network learning. This approach aims at employing the shallow learning on behalf of low precision and recall rates.

Biswas *et al*. [3], established an approach of automatic estimation of traffic density with the use of Single-Shot Detection (SSD) and Mobile Net. This is employed for processing various sizes and shapes of objects. The detection of average traffic density is made in this approach.

Harrou *et al.* [8], addressed a deep learning technique is addressed for the prediction of vehicle concentration. This technique is employed in the highly disaggregated prediction of vehicle concentration with the use of vehicle sensor. The data is being gathered from UK MI model. For analyzing the traffic conflicts, the regional CNN approach is employed.

For the recognition of traffic density, image global texture feature is introduced by [10]. The multi-scale block local binary pattern histogram (HMBLBP) is employed for analyzing the local features and in turn decreases the cost of computation.

Wang *et al*. [18] presented the monitoring and analysis of neural network traffic. An algorithm of multi-target pursuing is employed for processing the system in a detailed traffic. The tracking is then carried in an efficient manner for the traffic identification.

Bourouis *et al*. [4], suggested a traffic-sensing framework with the use of Bayesian network in 3D car models. In the multiple real-time application, scaled Dirichlet mixture model is employed for traffic sensing purposes.

Aljamal *et al*. [2], suggested a novel approach for traffic estimation stream density. Initially, the Artificial Neural Network (ANN) data driven approach is introduced for estimating the market penetration level (LMP) of the vehicles connected at two locations that are fixed. After that, the values estimated is employed as inputs for Kalman Filter (KF) for estimating the count of vehicles between two locations.

Saleem *et al*. [13], suggested an efficient and robust estimation of crowd density methods for its applied employment. In this broadside, a computationally economical and fine-tuned, ensemble regression-dependent machine learning model was presented for estimation of crowd density.

Agarwal *et al*. [1], an effectual convolutional neural network has been projected for estimating the density of traffic. By the same a new dataset of the labeled images was generated from footage of traffic video that are available.

Sadeq [12], presented high-resolution millimeter-wave (mmWave) radar sensor for attaining to obtain a richer radar point cloud representation relatively for a scenario of traffic monitoring.

Wang *et al*. [17], presented the traffic images that includes weather conditions, illuminations; vast scenarios were extracted from the system of current surveillance with the use of Shaanxi Province and in turn preprocessed for setting up a proper dataset for training. To perceive congestion of traffic, a structure of network is proposed depending on residual learning to be fine-tuned and pre-trained.

3. Pattern Matching for Vehicle Density Estimation (PMVDE)

The detailed narration of proposed methodology is described in this section. The process of proposed system is shown in Figure 1 below:

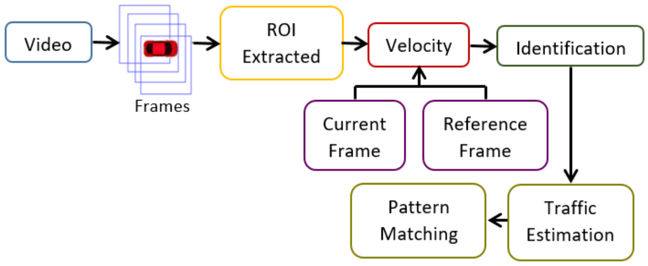

Figure 1. Process of PMVDE.

The traffic and road density investigation are carried out with the use of image processing technique. The image is obtained from the video. From the video, the image is being extracted as frames that consists of road images as input. In this approach, the pattern matching technique is employed for recognizing the road vehicles. This is analyzed by checking the image history that is kept in the database. The video that is extracted is positioned in each and every signal at particular kilometers for analyzing the traffic.

The main intention of this work is to monitor the density of traffic and to estimate the vehicle density. This in turn addresses the error rate. The density analysis performance is done by using the below four components. They are,

- ROI extraction.
- Speed monitoring.
- Identification of vehicle.
- Estimation of density.

On considering these four approaches, pattern matching is employed for matching the forgoing and current road pattern to achieve the outcome. The frames are extracted for every seconds from the video and the features are being extracted in ROI by taking the local and global features. The whole road is considered as global features while the patches of images are taken as local features.

3.1. Extraction of ROI (Region of Interest)

The extraction of ROI is the initial step. In this, the vehicles in the road are considered as interest and the region is density. The ROI is employed for the selection of essential regions of the road density is done by eliminating the information that are unnecessary like lane, tree and so on. This is expressed by the Equation (1)

$$r = \left[\frac{v_f + o}{o_d}\right] * n_f \quad (1)$$

From this equation the ROI is computed for the road density, where r is ROI, v is signified as a vehicle, v_f is denoted as vehicle features, and f denotes the image features. The road image is signified as o, d mentions to density, o_d is well-defined as the density of road, and n_f is an essential roadside vehicle feature.

3.2. Monitoring Speed

The speed is based on frame selection from video; consider the current frame and reference frame. In these frames, the current frame is having the vehicle in one patch either it is a right corner or left corner. Take the reference frame in such a way it has a difference from the current frame. The speed is estimated based on the time of splitting the two frames using Equation (2).

$$s_v = c_a - e_a * \sum\nolimits_{o=0}^{r=1} n_f + \frac{p_v}{o_d} \quad (2)$$

By using Equation (1), the ROI features are extracted, from the extracted features the speed is estimated using Equation (2). This is denoted as speed, s_v is the speed of the vehicle. Where, c_a represents the current frame and e_a refers to the reference frame. p is the position, p_v indicates the vehicle position. This equation is used for calculating the speed of the vehicle that is located within the extracted frame. The current and reference frame are subtracted to obtain the co-ordinate points of the vehicle within the extracted frame.

3.3. Vehicle Identification

The vehicle identification is carried out based on the pixels, frames of the input image. It is done through tracking the vehicle using its speed and extraction of ROI the following Equation (3) is used to evaluate the vehicle.

$$v_i = n_f + (c_a - e_a) * v_f \quad (3)$$

The velocity of the vehicle is evaluated, using Equation (3). Where i is denoted as identification, v_i is denoted as vehicle identification. In this way, the vehicle is identified from the road and it is further processed for analyzing the traffic on the road which is done on density estimation.

3.4. Density Estimation

The density estimation is considered by taking the road traffic control and how many vehicles are there on the road. The vehicle density is classified into Normal, Medium and Heavy. By using this density of traffic, it is monitored by deriving the following Equation (4).

$$d = \prod\nolimits_{o}^{v_i} \frac{p_v}{o_d} + \sum_{o=0}^{r=1} n_f + \left[p_v + (c_a - e_a)\right] \quad (4)$$

Based on the density estimation the traffic is regulated and the vehicle is been identified. The estimation consists of tracking the vehicles and routing the vehicle to the destination. In Equation (3), the vehicle is identified by using its pixel in the input frame after the vehicle is identified the density is used to calculate for traffic analysis. The density is observed using Equation (4), by considering its lane of the road using the previous information of data in the database. When few vehicles are found in the road means it is having the normal density, when there are having some vehicle indicates the medium. If multiple vehicles are identified, then the traffic density is considered as heavy.

3.5. Estimation of Pattern Matching-Road Density

The pattern matching recognizes the exact vehicle co-ordinates in the frame which is then compared with input data. In this approach, the pattern matching is employed for evaluating the estimation of road density. The intention of this approach is to estimate the distance among vehicles that are the two input image patterns. Figure 2 is the illustration of density estimation process using pattern matching.

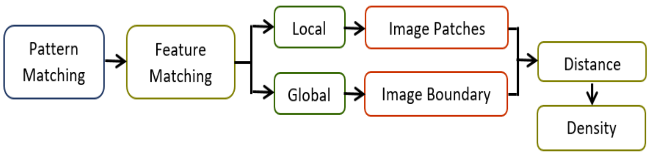

Figure 2. Density estimation using pattern matching.

By means of Euclidean distance the distance is examined among the image patterns uncertainty there are two vehicles are taken as v_1 and v_2. In this, v_1 is signified as a traffic sign and v_2 is the vehicle to recognize the distance from v_1. The two kinds of pattern matching is classified as: Feature Matching and Template Matching

In this approach, feature matching is done by considering both the local and global features. The local features comprise the patches of input image that are the block-dependent segmentation. From this block, the vehicle's single part is analyzed and extracted. The entire road is considered for global features. These features are expressed by means of the subsequent Equation (5).

$$m_f = v_f + p_v * \prod_{h}^{v} \begin{Bmatrix} l_f + g_f = t \\ l_f + g_f \neq t \end{Bmatrix} \tag{5}$$

On using Equation (4), the estimation of density is computed from the vehicles position. The position of vehicle is recognized through a technique of frame-based selection. From this, the pattern is being matched through Equation (5) m_f is represented as the feature's evolution and t is the earlier pattern observed. The global and local features are represented as g_f and l_f as the preceding pattern. The primary form is, $l_f+g_f=t$ gratifies once the features are coordinated with the patterns. The second condition $l_f + g_f \neq t$ signifies the features that are not matched.

By estimating the Euclidian distance, this is employed for identifying the process of matching that is equated in Equation (6). In the estimation of traffic density, the rectangular segment of road is being considered. The rectangular road segment consists of four vertexes, which has vehicles in all four vertexes. The intention is to identify the distance from first vertices to the second and so on. This in turn offers good computation of vertices by means of this scheme and in turn controls the traffic.

$$u = \sqrt{(xv_1 - a_o v_2)^2 - (yv_1 - b_0 v_2)^2} \tag{6}$$

From the Equation (5), vehicles features is estimated by considering the global and local features. On considering the Equation (6) the recognition of Euclidian distance of vehicle in the rectangular road vertices is made. x and y are denoted as the coordination of the vertices and u is denoted as Euclidean distance. Variables a_0, and b_0 are the pattern coordinates, the coordinates distance are tracked for two vehicles v_1 and v_2. Once the Euclidean distance is identified the features of pattern matching is intended whether it is min or max that is assessed in Equation (7).

$$\begin{aligned} j_v = {} & (x_1, a_0 \min) + (y_1, b_0 \max) + (x_2, a_0 \min) \\ & + (\mathrm{y}_2, \mathrm{b}_0 \max) + (x_3, a_0 \min) + (\mathrm{y}_3, \mathrm{b}_0 \max) \\ & + (x_4, a_0 \min) + (\mathrm{y}_4, \mathrm{b}_0 \max) \end{aligned} \tag{7}$$

By Equation (6) the distance is calculated from the rectangular vertices distance. From Equation (7), the error is reduced by gaining the coordinates that are having minimum error. j denotes the process of vehicles Pattern matching. (x_1, y_1) are symbolized as the first coordinates, (x_2, y_2), (x_3, y_3) and (x_4, y_4) specifies the second, third and fourth vertices' coordinates respectively.

From Equation (7) the min and max represent the minimum distance and maximum distance. The speed is examined after checking the traffic change in the road that are attained by computing the pattern matching approach. The pattern is not matched when there is no traffic in the road.

The process of matching is done by considering its features when the patches of the images are having two vehicles at the same time means the pattern matching process is evaluated. The matching is completed by having its pattern history. The features signify the classification of road pattern. If they are apart from the coordinates (x_4, y_4) and (a_0, b_0), then they are considered as the second chance of traffic categorizing them under heavy.

The density is used for recognizing the heavy traffic on observing the patterns and vertices coordinates. The normal, medium, and heavy traffic density estimation and the accuracy is enhanced by using Equation (8). It is employed for denoting the vehicle features in the coordinates and computing their speed for evading traffic in the road density.

$$j = \begin{Bmatrix} (l_f + g_f)_v + j_v < t \\ (l_f + g_f)_v + j_v > t \\ (l_f + g_f)_v + j_v = t \end{Bmatrix} \tag{8}$$

The vehicle patterns are recognized by means of Equation (7) then the traffic is being monitored by means of pattern matching process on using Equation (8). In the primary case, $(l_f + g_f)_v + j_v < t$ is employed once there are vehicles features, and patterns coordinates are having a smaller result matching which means they are intermediate traffic. The next case $(l_f + g_f)_v + j_v > t$ means the patterns are coordinated in this case the accuracy is enhanced in the process of pattern matching and density is heavy. The 3rd case $(l_f + g_f)_v + j_v = t$ employed when there is usual pattern matching is recognized.

From Equation (8) the accuracy is enhanced in a density estimation of vehicle. The work gratifies the two objects for example it decreases the error and improve the accuracy. The reduced error is attained by Equation (7) and accuracy is made by Equation (8). Equation (5) is employed for each image updated.

4. Performance Analysis

The proposed PMVDE system performance analysis is analysed with the use of experiments made by means of MATLAB. In this examination, random road traffic images are fetched from internet for which an extreme of 130ROI is perceived. The reference and current frames size are 800x600 and 1024x768 correspondingly. The number of fetched input is 8 and a process is repeated for every 40 iterations. In this study, the error rate, true and false positives, metrics accuracy are related with existing AVDCS [12] and HMBLBP [15] approaches.

4.1. Accuracy

The accuracy of the vehicle density detection in the projected PMVDE is greater through examining the reference and current input frames, varyingly. From the ROI, the relationship among the frames aids to categorize diverse features for detecting and classifying the individual vehicles. By means of the physical distance and velocity property as extracted from frames, the detection is improved in projected technique. Patterns are intra-frame and inter-frame matching for enhancing the detection rate to enhance accuracy. [Refer to Figure 3].

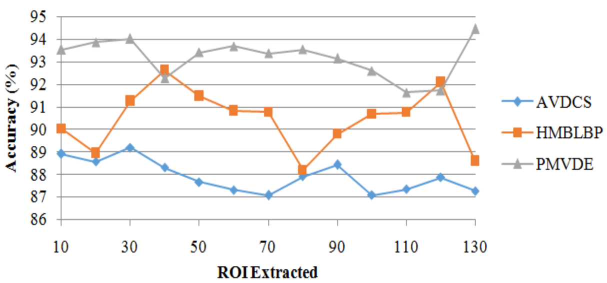

Figure 3. Accuracy.

4.2. Error Rate

The frames of pre-classification aids in differentiating non-overlapping and overlapping ROI from which precise detection is facilitated. The error number producing instances are recognized from both global and local features promptly. Based on the features matching, the true positives are distinguishing from true and false positives sum, decreasing the proposed method error rate [Refer Figure 4].

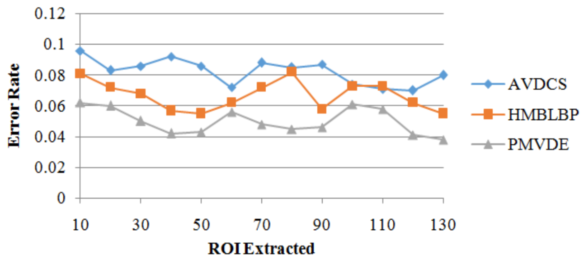

Figure 4. Error rate.

Table 1. Comparative analysis of false and true positive rate.

ROE Extracted	False Positive Rate		
	AVDCS	HMBLEBP	PMVDE
10	0.266	0.237	0.224
20	0.317	0.253	0.161
30	0.334	0.256	0.222
40	0.301	0.312	0.159
50	0.366	0.278	0.224
60	0.397	0.2	0.165
70	0.338	0.265	0.249
80	0.267	0.324	0.176
90	0.303	0.249	0.182
100	0.268	0.241	0.24
110	0.405	0.211	0.2
120	0.27	0.203	0.161
130	0.429	0.218	0.179
ROE Extracted	True Positive Rate		
	AVDCS	HMBLEBP	PMVDE
10	0.745	0.784	0.853
20	0.79	0.796	0.834
30	0.77	0.812	0.841
40	0.761	0.792	0.83
50	0.765	0.807	0.84
60	0.783	0.804	0.811
70	0.788	0.794	0.846
80	0.748	0.818	0.826
90	0.754	0.81	0.835
100	0.769	0.827	0.835
110	0.784	0.791	0.824
120	0.751	0.784	0.842
130	0.75	0.798	0.816

Table 2. Comparative analysis result tabulation.

Metrics	AVDCS	HMBLEBP	PMVDE
Accuracy (%)	87.27	88.611	94.458
Error Rate	0.08	0.055	0.038
Precision	93.30	93.89	94.62
Recall	90.51	90.97	91.44
F1-score	92.0	93.5	94.79

Table 3. Comparative analysis of precision, recall and F-score.

Metrics	AVDCS	HMBLEBP	PMVDE
Precision	93.30	93.89	94.62
Recall	90.51	90.97	91.44
F1-score	92.0	93.5	94.79

Table 1 provides the comparative analysis of false and true positive rate. The comparative analysis result tabulation is given in Table 2. The comparative analysis of precision, recall and F-score is tabulated in Table 3. Thus, from the analysis it was evident that the proposed system is better in offering enhanced rate of accuracy and decreased error rate on comparing other existing techniques. The proposed PMVDE result is compared with existing techniques like AVDCS and HMBLBP. From the compared result, it was evident that the proposed system is better in offering high accuracy rate, true positive rates, precision, recall, and F-score and lower rate of error values on comparing existing methods. Therefore, the presented scheme is said to be effectual than others in the detection of vehicle density using pattern matching scheme.

5. Conclusions

In this approach, vehicle estimation pattern matching is presented for enhancing the traffic monitoring system performance. In the process of density estimation, the ROI from the input frame is extracted for analyzing the features and templates matching. The vehicles were recognized initially from the ROI based on co-ordinate axis and physical features on employing reference and current frames. These methods are united to recognize the vehicle amount through exploiting the true positives and decreasing the false negatives for achieving better density estimation accuracy and decreasing the rate of error. Nevertheless, the suggested technique not focuses on time consumption process during inference. Hence, the future work focusses on implementing some advanced scheme that aims at time consumption of system.

References

[1] Agarwal A., Rana H., Vats V., and Saraswat M., "Efficient Traffic Density Estimation Using Convolutional Neural Network," *in Proceedings of the 6th International Conference on Signal Processing and Communication*, Noida, pp. 96-100, 2020.

[2] Aljamal M., Farag M., and Rakha H., "Developing Data-Driven Approaches for Traffic Density Estimation Using Connected Vehicle Data," *IEEE Access*, vol. 8, pp. 219622-219631, 2020.

[3] Biswas D., Su H., Wang C., Stevanovic A., and Wang W., "An Automatic Traffic Density Estimation Using Single Shot Detection (SSD) and MobileNet-SSD," *Physics and Chemistry of the Earth, Parts A/B/C*, vol. 110, pp. 176-184, 2019.

[4] Bourouis S., Laalaoui Y., and Bouguila N., "Bayesian Frameworks for Traffic Scenes Monitoring Via View-Based 3D Cars Models Recognition," *Multimedia Tools and Applications*, vol. 78, pp. 18813-18833, 2019.

[5] Chang H. and Cheon S., "The Potential Use of Big Vehicle GPS Data for Estimations of Annual Average Daily Traffic for Unmeasured Road Segments," *Transportation*, vol. 46, pp. 1011-1032, 2019.

[6] Chung J. and Sohn K., "Image-Based Learning to Measure Traffic Density Using A Deep Convolutional Neural Network," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 5, pp. 1670-1675, 2017.

[7] Guidoni D., Maia G., Souza F., Villas L., and Loureiro A., "Vehicular Traffic Management Based on Traffic Engineering for Vehicular ad Hoc Networks," *IEEE Access*, vol. 8, pp. 45167-45183, 2020.

[8] Harrou F., Zeroual A., and Sun Y., "Traffic Congestion Monitoring Using an Improved Knn Strategy," *Measurement*, vol. 156, pp. 107534, 2020.

[9] Hu H., Gao Z., Sheng Y., Zhang C., and Zheng R., "Traffic Density Recognition Based on Image Global Texture Feature," *International Journal of Intelligent Transportation Systems Research*, vol. 17, pp. 171-180, 2019.

[10] Husain A., Maity T., and Yadav R., "Vehicle Detection in Intelligent Transport System under A Hazy Environment: A Survey," *IET Image Processing*, vol. 14, no. 1, pp. 1-10, 2020.

[11] Jin F., Sengupta A., Cao S., and Wu Y., "MmWave Radar Point Cloud Segmentation using GMM in Multimodal Traffic Monitoring," *in Proceedings of IEEE International Radar Conference*, Washington, pp. 732-737, 2020.

[12] Sadeq H., "Using Total Probability in Image Template Matching," *The International Arab Journal of Information Technology*, vol. 17, no. 3, pp. 347-357, 2020.

[13] Saleem M., Khan M., Khurshid K., and Hanif M., "Crowd Density Estimation in Still Images Using Multiple Local Features and Boosting Regression Ensemble," *Neural Computing and Applications*, vol. 32, pp. 16445-16454, 2020.

[14] Sallay H., Bourouis S., and Bouguila N., "Online Learning of Finite and Infinite Gamma Mixture Models for COVID-19 Detection in Medical Images," *Computers*, vol. 10, no. 6, pp. 1-15, 2021.

[15] Stern R., Cui S., Delle Monache M., Bhadani R., Bunting M., Churchill M., Hamilton N., Haulcy R., Pohlmann H., Wu F., Piccoli B., Seibold B., Sprinkle J., and Work D., "Dissipation of Stop-and-Go Waves Via Control of Autonomous Vehicles: Field Experiments," *Transportation Research Part C: Emerging Technologies*, vol. 89, pp. 205-221, 2018.

[16] Tayara H., Soo K., and Chong K., "Vehicle Detection and Counting in High-Resolution Aerial Images Using Convolutional Regression Neural Network," *IEEE Access*, vol. 6, pp. 2220-2230, 2017.

[17] Wang P., Hao W., Sun Z., Wang S., Tan E., Li L., and Jin Y., "Regional Detection of Traffic Congestion Using in A Large-Scale Surveillance System Via Deep Residual Trafficnet," *IEEE Access*, vol. 6, pp. 68910-68919, 2018.

[18] Wang Y., Wang Q., Suo D., and Wang T., "Intelligent Traffic Monitoring and Traffic Diagnosis Analysis Based on Neural Network Algorithm," *Neural Computing and Applications*, vol. 33, pp. 8107-8117, pp. 1-11, 2020.

[19] Zheng. H, Chang W., and Wu J., "Traffic Flow Monitoring Systems in Smart Cities: Coverage and Distinguish Ability Among Vehicles," *Journal of Parallel and Distributed Computing*, vol. 127, pp. 224-237, 2019.

Sakthidasan Sankaran is an Professor in the Department of Electronics and Communication Engineering at Hindustan Institute of Technology and Science, India. He received his B.E. degree from Anna University in 2005, M.Tech. Degree from SRM University in 2007 and Ph.D. Degree from Anna University in 2016. He is a Senior Member of IEEE and member in various professional bodies. He is an active reviewer in Elsevier Journals and editorial board member in various international Journals. His research interests include Image Processing, Wireless Networks, Cloud Computing and Antenna Design. He has published more than 70 papers in Referred Journals and International Conferences. He has also published three books to his credits.